A Multi Objective Chance Constrained Programming Model for Intermodal Logistics with Uncertain Time

Maria Kalinina[1], Leif Olsson [2] and Aron Larsson[1,2]

[1] **Department of Computer and Systems Sciences, Stockholm University**
Kista, Stockholm SE-164 40, Sweden

[2] **Department of Information and Communication Systems, Mid Sweden University**
Sundsvall, Sweden

Abstract

This paper presents a multi objective chance constrained programming model for matching of goods and transports in an intermodal transport chain under uncertain delivery time. The objectives in the proposed model are cost, emission, and transport time, where time is considered as an uncertain parameter. An approach to solve the model is proposed, and this approach has been implemented in a web-based system for transport matching in order to provide clients with alternative transport routes in a large system of possible transport solutions. A case study of a Swedish shipping company is analyzed, and the results are presented through comparisons of results from deterministic and stochastic models. The suggested model can help a decision maker to select transport alternative compromising between time, cost, emission, and with respect to uncertainty in transport time parameters.

Keywords: *Decision Support Systems, Intelligent Transportation Systems, Logistics Network, Stochastic Multi Objective Optimization.*

1. Introduction

Modeling of an intermodal freight transport system is a more complex task than modeling a uni-modal system [1]. In an intermodal logistics environment, there are two main specificities of the decision problem which we consider. The first of these is conflicting objectives when jointly minimizing cost, time and emission. The second is the uncertainty associated with incompleteness of available data causing uncertainties. With respect to second specificity, we focus on the transport time between two transport nodes in the intermodal transport chain. The ways in which these both specificities are incorporated into previous approaches vary greatly.

For instance, efficient coordination using single objective optimization methods have been used for a long time. These methods focus on low cost, or short time or a mix of these, and a survey can be found in [2]. For the freight transport sector, many initiatives have been initiated such as promoting “green corridors” with one example being the “Mid Nordic Green Transport Corridor” [3]. A mapping of tools and/or techniques for green supply-chain management is found in [4].

Further, a great deal of research has been performed studying a single transport and the so-called “external costs” associated with the transport such as different types of emission costs and noise cost included [5], [6], [7]. In this case, efforts have been made in order to convert, for instance, carbon emission quantities and time quantities into a total cost in a life-cycle assessment and cost-benefit paradigm to be compared with other costs. This is similar to the way carbon emissions contracts are traded, for instance at the ICE ECX Emissions [8]. Succeeding with this would make the necessary optimization calculations again single objective and solvable in a straightforward manner using optimization methods. Unfortunately, it is not straightforward to fetch the needed inherent trade-offs in such approaches and the solution will not involve compromise amongst conflicting objectives. Other approaches instead consider multi objective, or multi criteria optimization, to address the general problem of assessing transport alternatives from many perspectives, cf., e.g., [9].

Accounting for parameter uncertainty may be handled by different approaches such as stochastic programming, fuzzy mathematical programming, probabilistic programming, or a combination of these approaches, cf., e.g., [10], [11], [12]. In an intermodal freight transport system, the uncertainty of transport time becomes crucial since there are multiple transportation times depending of several kinds of transports as well as several transportation companies. This paper, therefore, aims to formulate a multi objective optimization model taking uncertainty in transport time into account. The model proposed assumes that some information about uncertain time is available and that the mean and the standard deviation of the time random variable can be estimated in a reasonable way. Furthermore, the historical data of the transport time can be used to obtain estimates of future transport times.

The model is implemented in a web-based transport matching system and solved using the Lingo solver [13]. The model is tested on a small but illustrative case study of a Swedish shipping company in order to provide clients with alternative transport routes. Future practical extensions of the model will be based on the test of large size cases.

The paper is organized as follows. Section 2 contains the literature review of existing approaches in the intermodal systems. Section 3 is devoted to the basic concept. A multi objective chance constrained programming model is proposed in Section 4. In section 5, we present a solution approach. On a case study of a Swedish shipping company is demonstrated the proposed model and solution approach in section 6. Finally, Section 7 contains the conclusion and the sketch of some perspectives.

2. Related work

In this section, we summarize existing approaches for intermodal freight transportation systems which treated the multi criteria relationship between components and/or uncertainty of components.

In the context of joint minimization of cost and emission, Kim et al. [9] present a study of intermodal networks of different freight combinations; a truck-only system, a rail-based system, and a short sea-based system. The authors propose a two objective optimization model, which simultaneously minimize costs and the level of emissions subject to the demand and capacity. For simplicity reasons, the objective functions were expressed in a linear form, and the arising linear programming problem is solved by the Microsoft Excel solver. Six different scenarios that related to demand and capacity is studied, and it is shown that increasing the capacity of low emitting systems capacity will reduce emissions. However, the authors emphasized that a more precise formulation of the problem, leading to nonlinear programming could find a more accurate solution.

Park et al. [14] study the relationships between logistics cost, time and CO_2 emissions of the intermodal freight transportation systems. Their case study of the freight transportation systems of Korea involves the road network for trucks and the railway network. Minimizing of the total cost in the transportation network is conducted using linear programming optimization method with the CO_2 emission as constraints, and the relationship between all components is studied pairwise. The authors conclude that there are trade-off relationships between cost, time, and emission in the truck- and rail- based intermodal system.

Winebrake et al. [15] introduce the geospatial model, which can be used to analyze the cost, the delivery time, the energy and the environmental impacts of intermodal freight transports. Their network supporting truck, ship and rail transports routes may have multiple modes. Each route of the network is connected to dataset information about mode accessibility, operating cost, average speed, distance and emissions. Depending on a decision maker's goal, for instance the least-cost or shortest-distance, the corresponding single objective problem will be solved, and the result is to be analyzed by the decision maker. The authors demonstrate their approach on three case studies.

Moccia et al. [16] have focus on a multimodal transportation problem with timetables, flexible-time transportation, and consolidation options. Their suitable network representation of the problem is in the form of a directed graph where each arc is associated with related cost and traveling time. In order to solve the problem, a heuristic algorithm based on performing a time-limited branch-and-cut search on the set of generated columns is suggested. The final problem is an integer programming problem which is solved with the help of the MILP solver. The authors demonstrate the efficacy of the proposed approach on real-life data.

Notably, in the most of the models, the minimization of the transportation time and the uncertainty of transportation time are not considered. Moreover, these approaches do not incorporate the stochastic nature of the transport time and the use of historical data. In this paper, we therefore propose the multi objective chance constrained model in order to manage the inherent conflict between cost, emission and time, taking into account uncertainty of transportation time.

3. Background

3.1 The multi-objective optimization

The general multi objective optimization problem is stated in the following way:

$$\text{minimize } f(x) = (f_1(x), \ldots, f_k(x))$$

$$\text{subject to } x \in X$$

where $X \subset R^n$ is a feasible set of decision variables and is called the alternative space and the space R^n is called the variable space. The functions f_i, $i = 1, \ldots, k$, are objective functions (or criteria) such that

$$f_i : X \to R^k$$

where the space R^k is called the criterion space. The image of the feasible set $f(X) = \{q \mid q = f(x), x \in X\}$, is called a feasible criterion region, and the vector $f(x)$ is called an outcome vector. In this setting, we speak about an alternative $x \in X$ and the corresponding outcome vector of this alternative x, $f(x)$.

The following definitions will be taken into consideration.

Definition 1: An outcome vector $f(x)$, $x \in X$, is said to dominate another vector $f(y)$, $y \in X$, *if* $f_i(x) \leq f_i(y)$ for all $i = 1,\dots,k$, and the inequality is strict for at least one i. A vector $f(x)$ strongly dominates another vector $f(y)$ *iff* $f_i(x) < f_i(y)$ for all i.

Definition 2: A vector $f(x*)$, $x* \in X$, is non-dominated if there does not exist another $x \in X$ such that $f(x)$ dominates $f(x*)$.

Note that dominance relations relate to the concept of Pareto-optimality and efficiency.

Definition 3: An alternative is said to be Pareto-optimal, *iff* its outcome vector is not dominated by any other vector (which belongs to a feasible alternative). The corresponding vector is called efficient.

Definition 4: An alternative x is said to be a weak Pareto optimum, if there is no other feasible alternative y with an outcome vector $f(y)$ strongly dominating $f(x)$. The corresponding outcome vector $f(x)$ is called weakly efficient.

Obviously, weakly efficient outcomes are less desirable, but for the considered problem, weakly efficient outcomes can be taken into account due to that the identified efficient solution may be undesired due to factors not captured by the model. Reasons for searching efficient outcomes are explained in the solution approach's section 5.1.

3.2 Chance constrained multi objective optimization

Many parameters of a real-life problem are of a stochastic nature. In order to integrate the available stochastic information into an optimization problem formulation, chance constraints can be used. By using a chance-constrained optimization model, can be achieved system reliability under uncertainty [17].
The general chance constrained multi objective optimization problem can be formulated as follows

$$\text{minimize } f(x) = (f_1(x,\omega), \dots, f_k(x,\omega))$$

$$\text{subject to } x \in X,\ \Pr\{g_i(x,\omega) \leq \beta_i\} \geq \alpha_i$$

where $\omega \in \Omega$ are uncertain variables, $X \subset R^n$ is a feasible set of decision variables, and the real-valued random variables $f_i(x,\omega)$ with known joint distribution are defined on $X \times \Omega$, $i = 1, \dots, k$. Further, $g_i(x,\omega) \leq \beta_i$ refer to inequalities and $\alpha_i \in [0,1]$ are user-defined confidence levels.

If a chance constraint $\Pr\{g_i(x,\omega) \leq \beta_i\} \geq \alpha_i$ has the same confidence level for all i, then this is called a joint chance constraint. Joint chance constraints thus require a user-defined confidence level for the whole feasible region.
In an intermodal logistics environment, both kinds of chance constraints can be applied. The single chance constraints can help to handle uncertainty of each constraint individually. For instance, in the case when the transportation time on some leg is more crucial than for another leg. Furthermore, the joint chance constraints can be used in the case when information about some crucial legs is not available.

4. Problem description and proposed model

In intermodal logistics, there are trucks, trains and vessels involved on various sizes and used different types of engines and fuels. Some cargo is also transported by airplanes. The upcoming conflict between time, cost and emission objectives come from the fact that all involved parties have different interests and that different transport nodes have different properties and pros and cons that making the problem multi-objective in nature. For instance, if we consider medium length transports we have the following situation

- Trucks are fast, flexible but with high carbon emissions
- Electrical trains, usually used in Sweden, are slow in average speed with low carbon emissions
- Sea vessels usually take too long time for this transport but are otherwise very good in both cost and carbon emissions due to the vast amount of goods that can be transported one a single vessel.
- Airplanes are fast but in all other aspects not good. The emissions are not only high they are pollute with greenhouse gases on high altitude, which is even worse for the environment.

An intermodal distribution network consists of several distinct transport legs and several routes. The required information can be collected from the supplier and the shipping agent, and additional information regarding emissions can be calculated. The collected information can then be stored in a database. One main concern for intermodal transport logistics is that different load carriers must be on time at the intermediate nodes of the network for future transportation. The aim is to fill up the individual transport capacity on every leg used for the routes in the system that consist of empty or partial loaded load carriers. These load carriers can be added from databases or manually by the shipping agents in the system with the shipper's front-end in real-time.

The deterministic multi objective model has been proposed by Olsson and Larsson [18] and in Kalinina et al. [19] and is presented below.

Sets, Constants and variables

N	The set of all nodes defining the legs in the network with unique identities
R	The set of all routes in the network
$c^T_{ijpqmlk}$	The cost of transport on leg (i, j) with identity p, load carrier q for commodity m on route (l, k)
c^s_{lk}	The cost of shortage on route (l, k)
e_{ijpqm}	The actual emission on leg (i, j) vid identity p, load carrier q and commodity m
d^t_{lk}	The total demand on route (l, k)
m^{max}_{ijpqm}	The maximum transport volume on leg (i, j) for identity p, load carrier q and commodity m
m^{min}_{ijpqm}	The minimum transport volume on leg (i, j) for identity p, load carrier q and commodity m
t^{st}_{lk}	Start time for transport on route (l, k)
t^s_{ijpqm}	Start time on leg (i, j) with identity p, load carrier q for commodity m
t^t_{ijpqm}	Transport time on leg (i, j) with identity p, load carrier q for commodity m
$v_{ijpqmlk}$	Volume transported on leg (i, j) with identity p, load carrier q for commodity m on route (l, k)
s_{lk}	Shortage on route (l, k) e.g. the amount that can't be sent due to lack of transport capacity
e^{max}	The total calculated amount of emissions
d^s_{lk}	The demand sent on route (l, k)
t^{tot}_{lk}	Maximum transport time for a transport on route (l, k)

Decision variables

$x_{ijpqmlk}$	$x_{ijpqmlk}$ equals 1 if leg (i, j) with identity p, load carrier q for commodity m on route (l, k) is used, otherwise 0
f_{ijpqm}	f_{ijpqm} equals 1 if leg (i, j) with identity p, load carrier q for commodity m is used, otherwise 0

The deterministic multi objective mathematical model formulates as follows.

$$\min z_c = \sum_{(i,j,p,k,l)\in N} c^T_{ijpqmlk} v_{ijpqmlk} + \sum_{(k,l)\in R} c^s_{lk} s_{lk} \quad (1)$$

$$\min z_e = \sum_{(i,j,p,q,m,l,k)\in N} e_{ijpqmv} f_{ijpqm} \quad (2)$$

$$\min z_t = \sum_{(i,j,p,q,m,l,k)\in N} (t^s_{ijpqm} + t^t_{ijpqm}) f_{ijpqm} \quad (3)$$

s.t.

$$d^s_{lk} = d^t_{lk} - s_{lk},\ (l,k)\in R \quad (4)$$

$$\sum_{(i,j,p,q,m)\in N} v_{ijpqmlk} = d^s_{lk},\ j=k,\ (l,k)\in R \quad (5)$$

$$\sum_{(j,i,p,q,m)\in N} v_{ijpqmlk} = 0,\ j=k,\ (l,k)\in R \quad (6)$$

$$\sum_{(j,i,p,q,m)\in N} v_{ijpqmlk} = d^s_{lk},\ j=l,\ (l,k)\in R \quad (7)$$

$$\sum_{(i,j,p,q,m)\in N} v_{ijpqmlk} = 0,\ j=l,\ (l,k)\in R \quad (8)$$

$$\sum_{(i,j,p,q,m)\in N} v_{ijpqmlk} - \sum_{(i,j,p,q,m)\in N} v_{jipqmlk} = 0,$$
$$i\neq k,\ j\neq l,\ (l,k)\in R \quad (9)$$

$$\sum_{(l,k)\in R} v_{ijpqmlk} \leq m^{max}_{ijpqm},\ (i,j,p,q,m)\in N \quad (10)$$

$$v_{ijpqmlk} \leq m^{max}_{ijpqm} x_{ijpqmlk},\ (i,j,p,q,m)\in N,\ (l,k)\in R \quad (11)$$

$$v_{ijpqmlk} \geq m^{min}_{ijpqm} x_{ijpqmlk},\ (i,j,p,q,m)\in N,\ (l,k)\in R \quad (12)$$

$$t^{st}_{lk} - t^s_{ijpqm} \leq (t^{st}_{lk} + 1)(1 - x_{ijpqmlk})$$
$$i=l,\ (i,j,p,q,m)\in N, (l,k)\in R \quad (13)$$

$$t^s_{ijpqm} + t^t_{ijpqm} + t^t_{ijpqm} - t^s_{jnrqm} \leq$$
$$(t^s_{ijpqm} + t^t_{ijpqm})(2 - x_{ijpqmlk} - x_{jnrqmlk}),$$
$$j\neq k,\ n\neq i,\ r\neq p,\ (l,k)\in R \quad (14)$$

$$t^s_{ijpqm} + t^t_{ijpqm} - t^{tot}_{lk} \leq (t^s_{ijpqm} + t^t_{ijpqm})(1 - x_{ijpqmlk}),$$
$$j=k,\ (i,j,p,q,m)\in N, (l,k)\in R \quad (15)$$

$$x_{ijpqmlk} \leq f_{ijpqm} \quad (16)$$

$$f_{ijpqm} \leq \sum_{(l,k)\in R} x_{ijpqmlk} \quad (17)$$

$$\sum_{(i,m)\in N,(l,k)\in R} x_{ijpqmlk} \leq 1,\ (j,p,q)\in N \quad (18)$$
$$v_{ijpqmlk} \geq 0,\ s_{lk} \geq 0,$$

$$x_{ijpqmlk} \in \{0,1\},\ f_{ijpqm} \in \{0,1\} \quad (19)$$

The first objective function in (1) minimizes the total cost, the second objective function in (2) minimizes the total emission, the third objective function in (3) minimizes the total time. In constraints (4), the actual volume sent from supplier l to customer k equals the demand from supplier l at customer k minus the amount that can't be sent due to limits in the transportation system. Constraints (5) guarantee that the actual volume sent from supplier l to customer k is equal to the demand minus the unsent amount. Constraints (6) ensure that, in supplier node l, the sent volume is equal with the actual demand at the destination k. Constraints (7) enforce that in customer node (k) is received a volume that equals the actual sent volume from the supplier node (l) for the specific route (l, k). Constraints (8) guarantee that in a customer node cannot have that node as a supply node for that route. Constraints (9) ensure that whole the volume forwarded in the transshipment nodes. Constraints (10) are related to the load carriers current transport capacity. Constraints (11)

and (12) indicate maximal and minimal transport capacity for every volume variable, moreover, it indicates if a specific leg is used. Constraints (13) are time constraints for start node at the supplier; the arriving time has to be earlier than departing time from a node. Time constraints (14) ensure that the arriving time has to be earlier than departing time from a node for transshipment nodes, and time constraints (15) are designed for end node where the sent volume should be arrive no later than the pre-determined maximum transport time set by the supplier. Constraints (16) indicate that if a leg is used on any route it has to be related to a load carrier. Constraints (17) show that a load carrier can only be used if a transport is needed on that leg. Constraints (18) guarantee that transports are distinct for a route. Constraints (19) indicate that the variables for transported volume and the variable for the shortage is greater or equal to zero and are continuous; the variable indicating if a specific leg and transport carrier is used are binary variables.
To deal with the uncertainty of the time, we extend the model with chance constraints. We then consider the transportation time parameters at the nodes as stochastic parameters. In the model, uncertainties of time components are present in the time constraints and in the time objective function. Assume that the transport time t_{ijpqm}^{t} on leg (*i*,*j*) with identity *p*, load carrier *q* for commodity *m* components follows the normal distribution $N(\mu_{t_{ijpqm}}, \sigma^2_{t_{ijpqm}})$. According Charnes and Cooper [20], the stochastic coefficients in the objective function can be managed by using the expected value of those coefficients, and, thus, the time objective can be written

$$\min E(z_t) = \sum_{(i,j,p,q,m,l,k)\in N} (t_{ijpqm}^{s} + \mu_{t_{ijpqm}}) f_{ijpqm} \quad (20)$$

The time constraints (14) and (15) can be rewritten as follows.

$$t_{ijpqm}^{t}(x_{ijpqmlk} + x_{jnrqmlk}) \leq t_{ijpqm}^{s}(x_{ijpqmlk}+x_{jnrqmlk})+t_{jnrqm}^{s} \quad (14)$$

$$t_{ijpqm}^{t} x_{ijpqmlk} \leq t_{lk}^{tot} - t_{ijpqm}^{s} x_{ijpqmlk} \quad (15)$$

Then, the probability that transport time on leg (*i*,*j*) with identity p, load carrier q is a smaller than the value $t_{ijpqm}^{s}(x_{ijpqmlk}+x_{jnrqmlk})+t_{jnrqm}^{s}$ and it is bigger than a user predefined confidence level α, ($0\leq \alpha \leq 1$).

$$P(t_{ijpqm}^{t}(x_{ijpqmlk} + x_{jnrqmlk}) \leq t_{ijpqm}^{s}(x_{ijpqmlk}+x_{jnrqmlk})+t_{jnrqm}^{s}) \geq \alpha \quad (21)$$

A probabilistic form of the time constraints for the end at the customer (15) is

$$P(t_{ijpqm}^{t} x_{ijpqmlk} \leq t_{lk}^{tot} - t_{ijpqm}^{s} x_{ijpqmlk}) \geq \alpha \quad (22)$$

By the assumption, transport time t_{ijpqm}^{t} follows the normal distribution $N(\mu_{t_{ijpqm}}, \sigma^2_{t_{ijpqm}})$. Then, the deterministic equivalent to the chance constraints (21) are

$$\mu_{t_{ijpqm}} \leq t_{ijpqm}^{s}(x_{ijpqmlk}+x_{jnrqmlk})+t_{jnrqm}^{s} - \Phi^{-1}(\alpha)\, \sigma_{t_{ijpqm}} \quad (23)$$

Corresponding deterministic constraints to the chance constraints (22) are

$$\mu_{t_{ijpqm}} \leq t_{lk}^{tot} - t_{ijpqm}^{s} x_{ijpqmlk} - \Phi^{-1}(\alpha)\, \sigma_{t_{ijpqm}}, \quad (24)$$

where $\Phi^{-1}(\alpha)$ is inverse of the standard normal cumulative distribution.
Thus, the multi objective chance constrained model can be formulated using the equations (1), (2), (20), (4)-(13), (23), (24), (16)-(19) as described above.

5. Solution approach

The proposed reliable network model is a probabilistic constrained three objective mixed integer linear programming problem. In order to solve this model, we suggest the following approach.

5.1 The procedure for generating of non-dominated freight transport alternatives

A lot of methods have been developed for generating of Pareto optimal solutions in the case of a convex objective space, see, e.g., [21], [22], [23]. For a non-convex objective space, the ε-constraint method can be used as the generating method [24]. The ε-constraint method is based on minimizing one of the objectives and restricting the rest of the objectives within predefined values. To ensure Pareto optimality we should solve three different problems through perturbing of the upper bounds for those problems. In view of the non-convexity of the feasible set and for the need of a generating method, the ε-constraint method has been used. The multi-objective problem (1)-(19) and the multiobjective chance constrained problem can be thus reformulated as three single objective problems.

minimize $f_{cost}(x)$
s. t. $f_{emission}(x) \leq \varepsilon_e^{(2)} - \beta$, $f_{time}(x) \leq \varepsilon_t^{(2)} - \beta$, $x \in X$ (25)

minimize $f_{emission}(x)$
s. t. $f_{cost}(x) \leq \varepsilon_c^{(3)} - \beta$, $f_{time}(x) \leq \varepsilon_t^{(3)} - \beta$, $x \in X$. (26)

minimize $f_{time}(x)$
s. t. $f_{emission}(x) \leq \varepsilon_e^{(4)} - \beta$, $f_{cost}(x) \leq \varepsilon_c^{(4)} - \beta$, $x \in X$. (27)

The following procedure then generates Pareto optimal alternatives.

- *Initial step:* Set $\varepsilon_i^{(j)}$ sufficiently large, where $j \in \{2,3,4\}$, $i \in \{c, e, t\}$ and β sufficiently small.
- *Step 1:* Solve the optimization problems (25-27) with given $\varepsilon_i^{(j)}$. Let $x^*_{(2)}$, $x^*_{(3)}$, $x^*_{(4)}$ be solutions of problems (25-27) respectively.
- *Step 2:* If for all j shortage cost is not equal to zero stop, else $\exists j$ such as shortage cost is equal to zero, set $\varepsilon_i^{(j)} = f_i(x^*_{(j)})$ and go to step 1and solve the problem (j).

In the initial step, the values $\varepsilon_i^{(j)}$ can be selected using preference information from a decision maker, for instance, upper bounds for cost and time function can be desirable values and upper bound for emission function can be the accepted level of emission for company. With each new step, the found solutions will be forced to comply with the stronger restrictions. The solutions of problems (25)-(27) with such defined upper bounds will be efficient [24]. The solutions with nonzero shortage cost can be taking into consideration in the some cases. It is possible to see on which leg does not exist any amount of transports or on which leg is exceeding the maximal transport capacity. In this case, a new leg can be created by new shipping agents in the portal.

5.2 The procedure for generating of weak Pareto freight transport alternatives

In certain cases, the generated non-dominated alternatives do not meet a decision maker's requirements due to contracts, accidents or other circumstances. Then the generating of weak Pareto freight transport alternatives will be substantiated. Obviously, weakly efficient outcomes are less desirable. Nonetheless, when obtained Pareto optimal alternatives are useless due to that there are obstacles in the form of an accident on one leg or the weather situation, weakly Pareto optimal alternatives can be taken into consideration.
The procedure requires information from a decision maker about which objective function is deemed more important. Without loss of generality, we assume that the most important objective is the cost function and denote the desirable value of the cost function by ε. At this point, the multi-objective problem (1)-(19) and the multi objective chance constrained problem can be formulated in the form of two single objective problems as follows

minimize $f_{emission}(x)$
s. t. $f_{cost}(x) \le \varepsilon$, $f_{time}(x) \le \varepsilon_t^{(5)} - \beta$, $x \in X$. (28)

minimize $f_{time}(x)$
s. t. $f_{emission}(x) \le \varepsilon_e^{(6)} - \beta$, $f_{cost}(x) \le \varepsilon$, $x \in X$. (29)

The following procedure then generates the weak Pareto alternatives.

- *Initial step:* Specify a desirable value ε for desired objective function. Set $\varepsilon_i^{(j)}$ sufficiently large, where $j \in \{5,6\}$, $i \in \{e, t\}$ and α sufficiently small.
- *Step 1:* Solve the optimization problems (28-29) with given $\varepsilon_i^{(j)}$. Let $x^*_{(5)}$, $x^*_{(6)}$ be solutions of problems (28-29) respectively.
- *Step 2:* If for all j shortage cost is not equal to zero stop else $\exists j$ such as shortage cost is equal to zero, set $\varepsilon_i^{(j)} = f_i(x^*_{(j)})$ and go to step 1and solve the problem (*j*).

The procedure enables to find the solutions that are close to or less than the desired value of the objective function. Since the upper limit is perturbed only for one objective in the problems (28) - (29), the obtained alternatives will be weak Pareto optimal alternatives.

6. Case study

In this section, we present the result of applying our proposed approach on the real-life case study.

6.1 Case description

Today pellets are transported from the port of Söråker near Sundsvall in Sweden to places in the northern regions of Sweden. Pellets arrive with both trucks and trains to this port, but in this case we have only considered the distribution of Pellets out from this port to 8 customers with one hub on the way. The nodes for Pellets distribution for this case are depicted in Figure 1. The actual network of transport links consists of several time dependent transport links between the hub and the final destinations, including capacities, demand, and other constraints. In total, the transport links are 56, see Table 5. For instance, there are 15 transports available only between the node 1 and 2 in the network. Thus, the network consists of the legs that are the actual load carriers and the routes which can consist of one or more load carriers and many shifts between different transport modes.

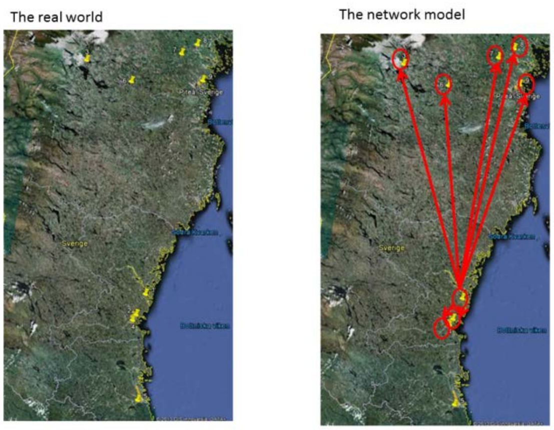

Figure 1: The real world map with some placeholders to the left indicating the nodes used in the case study. To the right the network is defined in this map

The web-based portal prototype has been developed for real time matching of cargo from suppliers with load carriers from the shipping agents, see Figure 2. Available information about cost, transportation time and emission, type of transports can be added manually or connected directly to a database for real time matching. We measure the costs in monetary terms, the carbon emissions in CO_2/mt and the time in hours. The data have been taken from the real world data flow at the company, and the carbon emissions on a single leg in the pellets transport system was calculated by the Ecotransit calculator [25].

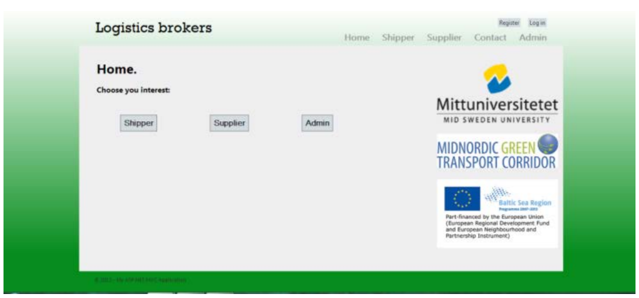

Figure 2: The front page of the demo of the portal for matching cargo from suppliers with load carriers from the shipping agents.

With this suggested approach and the MILP solver, the necessary calculation can be performed in real time and suggestions for transports will be presented to the supplier instantly in the web portal. In Figure 3, data received from the shipping agents for the pellets case are visualized.

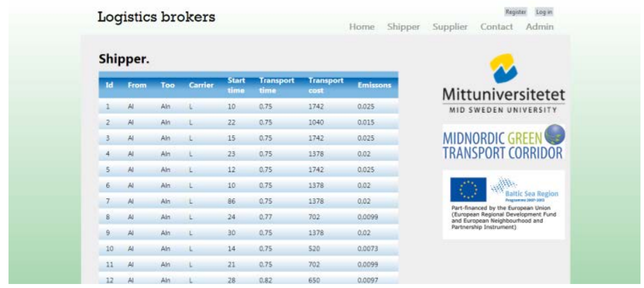

Figure 3: The portal from the shipping agents point of view for the pellets case.

The corresponding mathematical model has 927 variables, 392 integer variables and 1926 constraints. The Lingo solver [13] was used for the calculation.

6.2 Result and Analysis of Case Study

We compare the solutions to the stochastic model with solutions to the deterministic model. Solutions to the deterministic model are reported in Table 1.

Table 1: Pareto optimal alternatives from deterministic model

Transport alternatives	***Cost***	***Time***	***Emission***
A	29130	155,58	0,582
B	29194	152,58	0,588
C	29337	151,58	0,598
D	29401	148,58	0,604
E	29930	163,58	0,576
F	30474	138,58	0,607
G	30681	134,58	0,623

It can be noted that the solution will have lowest emission with highest time. If one focuses on the minimal time, the solution will often have high cost and a high emission. In other words, cost, time, and emissions are not independent. There are various relationships between them. The relationship between cost and emission indicates that reduction of cost is not always accompanied also reduction of emissions, for instance alternative *D* has highly emission and lowly cost and time values than alternative *E*. There are trade-offs relationships between cost, time and emission, where improvements in the cost or the emission dimensions cannot occur without impairment of the time dimension. The compromise between cost, time and emission should be considered in order to meet the needs of various interests. Solutions to the stochastic model are reported in Table 2.

Table 2: Pareto optimal alternatives from stochastic model

Transport alternatives	***Cost***	***Time***	***Emission***
C_s	29337	155,08	0,598
D_s	29401	152,08	0,604
I	30137	163,08	0,592
G_s	30681	138,08	0,623

Obviously, different efficient solutions are obtained from the deterministic and the stochastic model. We can, however, conclude that alternatives C_s, D_s and G_s are robust since they differ only by the total travel time and have the same cost and emission. Additionally, a new Pareto optimal alternative *I* is revealed from the stochastic model. Alternative G_s has the highest cost and the highest emission but the lowest transportation time, and it may be suitable if finally selected alternative should be have the least travel time.

In the case when the identified alternatives do not meet the needs of a decision maker, the procedure for generating of weak Pareto alternatives may be applied. With the procedure was created six weak efficient solutions, see Table 3. The alternatives *A1, B1, C1, D1, F1,* and *G1* have the same emission and time as alternatives *A, B, C, D, F* and *G* but higher cost. These dominated alternatives may be relevant. Out of the alternatives obtained from the procedure for generating of weak optimal Pareto alternatives, the solutions *A1, B1,C1,D1,F1,G1* differ from solutions *A,B,C,D,F,G* on costs values, i.e. they can be considered as a complementary to each other. It is, however, important to note that alternatives *A1-G1* are weak Pareto optimal and the procedure should be applied in the case when the desirable alternatives could not be selected from non-dominated alternatives *A-G*.

Table 3: Weak Pareto optimal alternatives from deterministic model

Transport alternatives	***Cost***	***Time***	***Emission***
A1	29162	155,58	0,582
B1	29226	152,58	0,588
C1	29369	151,58	0,598
D1	29433	148,58	0,604
F1	30506	138,58	0,607
G1	30713	134,58	0,623

However, from a practical point of view, if time instances of uncertain situation could be taken into account, then, applying the procedure for generating weak Pareto optimal alternatives from multi objective chance constrained model can be used. In this case, we have four alternatives C_{ws}, D_{ws}, G_{ws} which differ from alternatives *C1, D1, G1* only on travel time component, see Table 4.

Table 4: Weak Pareto optimal alternatives from stochastic model

Transport alternatives	***Cost***	***Time***	***Emission***
C_{ws}	29369	155,08	0,598
D_{ws}	29433	152,08	0,604
I	30137	163,08	0,592
G_{ws}	30713	138,08	0,623

Despite this small amount of data, we can see that in the case when minimizing the travel time, we identify a different alternative in the stochastic optimization than for the deterministic case. This indicates that in real cases with large data sets, it is likely that undesirable alternatives will be promoted by the system if the uncertainty with respect to transportation time is not taken into account.

The result obtained from a set of real data can be analyzed by a decision maker. In this case study, there are few alternatives from the stochastic model, and decision makers can select desirable transport alternative from this set of alternatives. In the case when the obtained sets of Pareto optimal and weak Pareto optimal alternatives are large, additional procedures for finally selecting a desirable alternative is needed. A candidate procedure for the selection of an alternative from the Pareto set is presented in [26]. This procedure allows selecting an alternative based on complete or incomplete preference information from a decision maker and, thus, is complementary to the above suggested approach.

With respect to achieving low carbon transports in intermodal logistics, the proposed approach allows to view for shippers and suppliers emission related information and select the alternative in relation to emission, cost and time aspects. The possibility to use a system like the portal presented in this paper in order to match shipping agents empty volume to available cargo using an automatized optimization routine enable for larger utilization of carriers and thus a more effective value chain. By using the approach with multi-objective optimization enable for weighing carbon emissions against other objectives. In this manner, low carbon transports that meet other requirements of a supplier can be identified. From the results, it is obvious that solutions that have been lost when focusing on only one single objective at a time. Further, since the three objectives are dependent, an ordinary single objective approach cannot handle these interdependencies in a consistent manner, and, therefore, the use of multi-objective optimization is a good candidate for formal problem modeling. A distinctive feature of the suggested approach is the possible reduction of carbon emission achieved by stipulating a restriction on the emission level in the optimization model, and that finally selected alternative will be a compromise between cost, time and emission objectives.

With respect to handling uncertainty of transportation time in intermodal logistics, the proposed approach allows to view for shippers and suppliers robust time related alternatives and relate this to cost and emission aspects when suggesting transport alternatives.

The result of this case study shows that by using the proposed model, we can deal with uncertainty in the time components, in addition handling of uncertainty can be based on historical data of transportation time. Developed procedures can make the portal very flexible for the suppliers that want the transports. Therefore, managing simultaneously cost, time and emission and handling uncertainty of transportation time parameters will satisfy both the shipping agent and supplier and contribute to a sustainable and scalable transport system in the future.

7. Conclusions

In this paper, we have developed a multi objective chance constrained programming model for the matching of goods and intermodal transports alternatives in the presence of conflict between time, cost and emission under uncertainty in the delay time. The model supports simultaneous minimization of cost, time and emission. To demonstrate the model, a case study of a Swedish shipping company is presented as a proof-of-concept. The future implementation of this model is a promising decision support framework for matching goods with intermodal transports alternatives. Result from the proposed model can be the alternative which has a slightly longer travel time, but it will be more reliable and thus preferred. The contribution of our work is that the solution results from the developed model can provide a substantial economic potential with reliable decision based on handling uncertainty using historical data and taking into account conflict between objectives.

Appendix

Appendix 1

Table 5: Nodes at intermodal points

Node	***City***	***Number links***
1	Älandsbro	0
2	Alnö	15
3	Arjeplog	10
4	Arvidsjaur	5
5	Bergvik	1
6	Boden	14
7	Sidsjön	8
8	Sundsvall	3

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